FX Liquidity Risk and Carry Trade Returns

Samuel Abankwa *

Lloyd Blenman†

Abstract

We study the effects of FX liquidity risk on carry trade returns using a low-frequency market-wide liquidity measure. We show that a liquidity-based ranking of currency-pairs can be used to construct a mimicking liquidity risk factor, which helps in explaining the variation of carry trade returns across exchange rate regimes. In a liquidity-adjusted asset pricing framework, we show that the vast majority of variation in carry trade returns during any exchange rate regime can be explained by two risk factors (market risk factor and liquidity risk factor) in the FX market. Our results are further corroborated when the hedged liquidity risk factor is replaced with a non-tradeable innovations risk factor. We further provide evidence that liquidity risk is priced in the cross-section of currency returns, and estimate the liquidity risk premium in the FX market to be around 412 basis points per annum.

JEL Classifications: C10, F31, G12, G15

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*Vice President, Quantitative Analytics Consultant, Wells Fargo Bank, 301 S College Street, Charlotte, NC 28202. Phone: (704) 715-8891; E-mail: samuel.abankwa@wellsfargo.com.

†Professor of Finance, Belk College of Business, University of North Carolina, 9201 University City Blvd, Charlotte, NC 28223. Phone: (704)687-7705; E-mail: lblenman@uncc.edu.

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1 Introduction

Liquidity in equity and bond markets has been studied extensively in the finance literature [1]. This cannot be said about liquidity in the foreign exchange (FX) market. This is puzzling considering the fact that the FX market is the world's largest financial market with an estimated average daily trading volume of about $5.3 trillion U.S. dollars in 2013 (BIS, 2013), which corresponds to about 10 times the size of global equity markets (WFE, 2013).

Market liquidity is an important feature for the well-functioning of all financial markets, yet little is known about FX liquidity and its co-movement with individual currency-pairs. A quick view into the global financial crisis of 2007-2009 sheds some light on this. Liquidity in money markets declined significantly following credit rationing in the interbank markets. This was due to the fact that banks refused to lend to each other because of funding liquidity problems relating to uncertainty over their exposure to structured products. The amount of exposure was a significant consideration because market liquidity of these structured assets had declined significantly, thereby reinforcing difficulties in valuing such structured products (Ivashina & Scharfstein, 2010).

Liquidity and its converse, illiquidity, are elusive concepts. A liquid security is characterized by the ability to buy or sell large quantities of it at a low cost. A good example is U.S. Treasury bills, which can be sold in blocks of $20 million dollars instantaneously at the cost of a fraction of a basis point. On the other hand, trading an illiquid security is difficult, time-consuming, and costly. Illiquidity is observed when there is a large difference between the offered sale price and the bid (buying) price, if trading of a large quantity of a security moves its price by a lot, or when it takes a long time to liquidate a position. Liquidity risk is the risk that a security will be more illiquid when its holder needs to sell it in the future, and a liquidity crisis is a time when many securities become highly illiquid at the same time (Amihud, Mendelson, & Pedersen, 2013). In short, liquidity risk is uncertainty in liquidity level.

Academic research used to ignore liquidity. The theory assumed frictionless markets which are perfectly liquid all of the time. This paper takes the opposite view. We argue that illiquidity is a central feature of the

[1] Chung and Chuwonganant (2014) show that stock market uncertainty as measured by VIX exerts a large market-wide impact on liquidity. Amihud and Mendelson (1986), Chordia, Roll, and Subrahmanyam (2001), among others, use trading activity and transaction costs to study daily liquidity in equity markets. Hasbrouck (2009) estimates the effective cost of trades by relying on the spread model of Roll (1984). Pastor and Stambaugh (2003) measure stock market liquidity using return reversal, and show that liquidity risk is priced in the cross-section of stock returns. Goyenko, Holden, and Trzcinka (2009) compare various proxies of liquidity against high-frequency benchmarks. Chordia, Sarkar, and Subrahmanyam (2005), Fleming and Remolona (1999), among others, provide related studies for U.S. government bond markets. Green, Li, and Schurhoff (2010) study municipal bond markets, Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhutter, and Lando (2012) study liquidity effects in corporate bond markets.

securities and financial markets. Recent events of the global financial crisis of 2007-2009 support this study. The importance of liquidity risk was re-emphasized by the former Chairman of the United States Federal Reserve Bank, Ben Bernanke, at the Chicago Federal Reserve Annual Conference on Bank Structure and Competition on May 15, 2008: "Some more-successful firms consistently embed market liquidity premiums in their pricing models and valuations. In contrast, less-successful firms did not develop adequate capacity to conduct independent valuations and did not take into account the greater liquidity risks posed by some classes of assets." This paper is also motivated by Burnside (2008), who suggests that liquidity frictions may explain the profitability of carry trades because liquidity spirals can aggravate currency crashes.

In studying currency crashes from the recent financial crisis, Brunnermeier, Nagel, and Pedersen (2008) highlight the importance of liquidity in the FX market [2]. A decline in FX liquidity impacts currency carry traders and triggers liquidity spirals. Carry trades are investments where investors borrow from low interest rate capital markets and invest in high yield markets capitalizing on the interest rate differential [3]. There are prominent ways of executing the carry trade strategy. First, investors may borrow from the low interest rate capital market, and invest in a high yield market, to make arbitrage profits from the interest rate differential. As long as the investment currency does not depreciate against the funding currency, profits are positive (Galati, Heath, & McGuire, 2007) and (Zhang, Yau, & Fung, 2010). A second strategy is to exploit the forward premium, which is the difference between the forward exchange rate and the spot exchange rate of two currencies (Brunnermeier et al. (2008); Burnside, Eichenbaum, and Rebelo (2009))[4].

This paper provides a comprehensive study that links liquidity risk to carry trade returns and provides an explanation of why currency investors should consider and manage FX liquidity risk. The paper contributes to the international finance and empirical asset pricing literature in three major perspectives. This is the first study to investigate the effects of liquidity risk on carry trade returns across exchange rate regimes, using a low-frequency market-wide liquidity measure constructed from daily transaction prices. The possibility of using a low-frequency (LF) liquidity measure circumvents the restricted and costly access of intraday high-frequency (HF) data. Not only is access to HF data limited and costly, it is also subjected to time-consuming handling, cleaning, and filtering techniques. Second, we show that FX liquidity risk can be gleaned from the low-frequency market-wide liquidity measure, which helps in explaining the variation of carry trade returns in an asset pricing framework. Third, we find that liquid and illiquid G10 currencies behave differently toward

[2] Avery (2015) writes about the decision taken by the Swiss National Bank to unpeg the Swiss franc from the euro and the devastating effect on the country's private banks, leading to market liquidity drying up in the eurozone.

[3] The low interest rate capital market currency is known as the "funding currency" and the high yield market currency is referred to as the "investment currency".

[4] A third strategy of carry trade makes use of options and futures contracts as documented by Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Christiansen, Ranaldo, and Soderlind (2011), Andersen, Bollerslev, and Diebold (2007), and (Jorion, 1995).

liquidity risk for all regimes in this study. Whereas liquid currencies such as the JPY and EUR are not that sensitive to liquidity risk, illiquid currencies such as the AUD and NZD are highly sensitive to liquidity risk. Liquid currencies have negative liquidity betas whereas illiquid currencies show positive liquidity betas. This also substantiates the finding by Mancini, Ranaldo, and Wrampelmeyer (2013) that negative liquidity beta currencies act as insurance or liquidity hedge, whereas positive liquidity beta currencies expose currency investors to liquidity risk.

Our empirical asset pricing results suggest the presence of a statistically and economically significant risk premium associated with systematic FX liquidity risk. This risk premium is estimated to be around 4.12 percent per annum. The market price of liquidity risk stays significant after controlling for other common risk factors in the FX market. This validates the hypothesis that liquidity risk is priced in the cross-section of currency excess returns.

The remainder of this paper is organized as follows: Section 2 discusses the related literature, section 3 describes the data set and construction of the liquidity measures. In section 4, we run the currency-pair liquidity sensitivity regressions and rank the currencies in our sample. We also estimate the two-factor liquidity-adjusted model, run the Fama-MacBeth procedure and report research findings, and section 5 concludes.

2 Related Literature

Liquidity is an important feature of financial markets, yet little is known about its evolution over time or about its time-series determinants. A better understanding of these determinants might increase investor confidence in financial markets and thereby enhance the efficiency of corporate resource allocation.

Notwithstanding the importance of research on liquidity, existing studies of trading costs have all been performed over short time-spans of three years or less. This is probably due to the tedious task of handling voluminous intraday data and the paucity of intraday data going back in years. As a result, there are a number of questions for which research has not yet provided good answers. Among some of these questions are; what causes daily movements in liquidity and trading activity? Are they induced by changes in interest rates or volatility? How are asset returns affected as a result? Given the relationship between liquidity and asset returns, answering the above questions could shed light on the time-series behavior of currency market returns. Satisfactory answers most likely depend on a sample period long enough to subsume a variety of events, for only then could one be reasonably confident of the results and inferences.

Studies connecting liquidity to asset pricing in the equity and bond markets have evolved over time and are currently based on a twofold proposition that the level of illiquidity and illiquidity risk are priced. One of the initial studies pioneering the former aspect of liquidity is of Amihud and Mendelson (1986), they showed a positive relationship between an asset's level of illiquidity and expected returns. Pastor and Stambaugh (2003) elaborated further on Amihud and Mendelson's study of the level of illiquidity and demonstrated a link between asset returns and liquidity risk. Amihud (2002) investigated systematic illiquidity risk and proposed that expected market illiquidity is priced positively, while shocks to market illiquidity lower contemporaneous returns. Amihud (2002) provided this evidence for the U.S. market, whereas Bekaert, Harvey, and Lundblad (2007) tested these hypotheses for the emerging markets. Bao et al. (2011) show that the illiquidity in corporate bonds is substantial, significantly greater than what can be explained by bid-ask spreads.

In their study, Pastor and Stambaugh (2003) find that stocks whose prices decline when the market gets more illiquid receive compensation in expected returns. Dividing stocks into ten portfolios based on liquidity betas, the portfolio of high-beta stocks earned 9% more than the portfolio of low-beta stocks after accounting for market, size, and value-growth effects with the Fama-French 3 factor model. This paper follows a similar methodology using currency-pairs instead of stocks [5], and constructing a liquidity risk factor, which helps in explaining the variation of carry trade returns across exchange rate regimes.

Acharya and Pedersen (2005) performed a similar but general investigative study to that of Pastor and Stambaugh (2003). They form 25 portfolios sorted on the basis of previous year's liquidity (liquidity of individual stocks). They find that in general, expected returns are higher for stocks that are illiquid on average. Documented average returns range from 0.48% to 1.10% per month as the illiquidity of the portfolios rises.

Currency carry trade is a trading strategy which consists of selling low interest-rate currencies (funding currencies) and investing in high interest-rate currencies (investment currencies). While the uncovered interest rate parity (UIP) hypothesizes that the carry gain due to the interest-rate differential is offset by a commensurate depreciation of the investment currency, empirically the reverse holds, namely, the investment currency appreciates a little on average with a low predictive R^2 as documented by Fama (1984). This violation of the UIP - often referred to as the "forward premium puzzle" - is precisely what makes the carry trade profitable on average.

[5]Following Papell and Theodoridis (2001), our numeraire currency for the ten currency-pairs is the U.S. dollar (USD). We recognize that there might be slight differences across currency numeraires, but we make our choice based on the dominance of the U.S. dollar in world financial markets. We expect that our main results will be invariant to the choice of currency numeraire.

Brunnermeier et al. (2008) show that carry traders are subject to crash risk. They argue that crash risk as measured by negative skewness is due to sudden unwinding of carry trades, which tend to occur in periods in which risk appetite and funding liquidity decrease. Burnside et al. (2009) and Lustig, Roussanov, and Verdelhan (2011) show that traditional risk factors in the exchange rate market cannot explain carry trade returns. These risks are either not correlated with carry trade returns or are too small to explain the carry trade profit. Burnside, Eichenbaum, and Rebelo (2011) confirm that traditional factor models, like CAPM and Fama and French 3-factor model, are not helpful in capturing the risk factors in carry trade.

Lustig and Verdelhan (2007) sort currencies into portfolios according to their forward discount and define risk factors to price the portfolios. Lustig et al. (2011) discuss an alternative way to define risk factors. They were motivated by the stock returns literature, like Fama and French (1993), in which risk factors are derived from particular investment strategies or stock returns. Lustig et al. (2011) propose a single global risk factor that explains most of the variation in the excess return between high and low interest rate currencies. Our liquidity risk factor (IML) for the whole sample period is strongly correlated (0.84) with their global risk factor. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) establish that global foreign exchange volatility risk offers the best explanation of cross-sectional excess returns of carry trade portfolios. Mancini et al. (2013) use a high-frequency (HF) market-wide liquidity measure constructed from intraday data from 2007 to 2009, and they show that funding currencies offer insurance against liquidity risk, while investment currencies offer exposure to liquidity risk. This is consistent with our finding of liquid and illiquid currencies, respectively exhibiting low and high exposure to liquidity risk. Whereas the studies above use a shorter time period that includes financial crisis when liquidity issues are likely to be important, our study uses 15 years of data to investigate the role liquidity risk plays in explaining carry trade returns in both "normal" and times of stressful market conditions.

3 Data & Methodology

We collect daily nominal exchange rates to the U.S. dollar (USD) and 1-month deposit interest rates from Bloomberg from December 1998 to July 2015 for ten major developed markets: Eurozone (EUR), Great Britain (GBP), Canada (CAD), Japan (JPY), Switzerland (CHF), Australia (AUD), New Zealand (NZD), Norway (NOK), Sweden (SEK), and Denmark (DKK). Missing data for some of the currencies, especially illiquid NOK and NZD, are imputed before constructing the daily liquidity measures. EM imputation (Expectation Maximization), PCA imputation, and mean imputation were implemented for missing data. Of the three methodologies, the PCA gave minimum absolute error and mean squared error and was therefore used to handle all daily missing data[6]. For each trading day, the midpoint of the bid and ask quotes, low and high transaction prices, and close prices are used to construct the liquidity measures and carry trade returns. Daily 1-month country deposit rates are used to construct the carry trade returns as shown in equation (11). We also collect data from Bloomberg on the Deutsche Bank's G10 DB Currency Harvest (DBV) Carry Index Fund. This is used for a robustness check to ascertain that our liquidity risk factor constructed can explain the variation of index fund returns across exchange rate regimes.

Following Bullard (2012), we divide our sample into exchange rate regimes using Lehman Brother's collapse on September 15, 2008, as a reference point of gauging how liquidity measures respond to market dislocations. The rationale for using different sample periods is to test whether carry trade returns are driven by financial crisis or economy events across exchange rate regimes. Although the major events of the global financial crisis occurred during 2007 to 2009, the post-crisis period in this paper still captures some of the market crisis spillovers. For instance, on November 22, 2010, the EU/IMF authorities unanimously agreed to a three year joint financial assistance programme for Ireland. Fannie Mae on May 10, 2010, reports a net loss of $11.5 billion in the first quarter of 2010. The U.S. Treasury Department announced on March 21, 2011, to sell about $142 billion of the agency-guaranteed mortgage-backed securities (MBS). The effects of all these events on the market were considered in the construction of the crisis and post-crisis periods/regimes.

3.1 Constructing Liquidity Measures

3.1.1 Roll 1984 Bid-Ask Bounce

The first liquidity measure used in this study is Roll (1984) bid-ask bounce estimation of transaction costs. Roll (1984) argues that trades hit either bid or ask prices and this bid-ask bounce induce a first-order negative serial dependence in successive observed market price changes. Given market efficiency, Roll (1984) deduced the effective bid-ask spread as:

$$Spread = 2\sqrt{-Cov\left(\Delta S_t, \Delta S_{t-1}\right)} \tag{1}$$

where "Cov" is the first-order serial covariance of price changes and S_t is the transaction price at time t. This measure is directly linked to liquidity, the higher the Roll spread, the lower is the liquidity. In deriving

[6]The Expectation-Maximization methodology of imputing missing data uses the E-M Algorithm. This is an interactive procedure in which other variables (in this case other currency-pairs) are used to impute a value (expectation), then the algorithm checks whether that is the value most likely (maximization). If not, it re-imputes a more likely value. This goes on until it reaches the most likely value. Pigott (2001) shows that EM imputation is better than the mean imputation because EM preserves the relationship with other variables, which is vital if employing Factor Analysis or Regression. Mean imputation is the replacement of a missing observation with the mean of the non-missing observations for that variable. The Principal Components Analysis (PCA) approach creates a model of non-missing data matrix. The eigenvector decomposition is then used to estimate the missing data points. In doing so, the score of the principal component and factor loadings are used.

equation (1), Roll (1984) denotes V_t as the unobservable fundamental value of the stock on day t. Assume that this fundamental value evolves as a random walk.

$$V_t = V_{t-1} + e_t \tag{1.1}$$

where e_t is the mean-zero, serially uncorrelated public information shock on day t. Next, let S_t be the last observed trade price on day t. Assume that S_t is determined by

$$S_t = V_t + \frac{1}{2}CQ_t \tag{1.2}$$

where C is the effective spread or cost and Q_t is a buy/sell indicator for the last trade that equals +1 for a buy or -1 for a sell. Q_t is equally likely to be +1 or -1, and is serially uncorrelated, and independent of e_t. Taking the first difference of equation (1.2) and combining it with equation (1.1) yields

$$\Delta S_t = \frac{1}{2}C\Delta Q_t + e_t \tag{1.3}$$

where Δ is the change operator. Given this setup, Roll (1984) shows that the serial covariance is

$$Cov\left(\Delta S_t, \Delta S_{t-1}\right) = \frac{1}{4}C^2 \tag{1.4}$$

Solving equation (1.4) for C gives Roll's estimator in equation (1).

3.1.2 Goyenko et al. (2009) Liquidity Measures

Goyenko et al. (2009) argue that daily price changes exhibit positive serial dependence some times and hence modified the Roll (1984) measure. Harris (1990) first documented the ill-behavior of the Roll (1984) spread estimator. He finds that the serial covariance estimator yields poor empirical results when used to estimate individual security spreads. Estimated first-order serial covariances are positive for about half of all securities so that the square root in the estimator is not properly defined. Harris (1990) concludes that the serial covariance estimator is very noisy in daily data and is biased downward in small samples.

Goyenko et al. (2009) modified the Roll (1984) measure so that if first-order serial covariance is positive, it will still be defined.

$$\text{Modified Roll} = \begin{cases} 2\sqrt{-Cov\left(\Delta S_t, \Delta S_{t-1}\right)} & \text{when } Cov\left(\Delta S_t, \Delta S_{t-1}\right) < 0 \\ 0 & \text{when } Cov\left(\Delta S_t, \Delta S_{t-1}\right) \geq 0 \end{cases} \tag{2}$$

Goyenko et al. (2009) also propose an effective spread measure in their horse race liquidity study and find that this measure performs well with high frequency data.

$$\text{Effective Spread} = 2\,|ln(S_t) - ln(M_t)| \tag{3}$$

where M_t is the mid-quote price at time t.

3.1.3 Hasbrouck's Gibbs Measure of Roll 1984

Hasbrouck (2009) advocates a Bayesian estimation of Roll (1984) model using Markov chain Monte Carlo (MCMC) estimator, the Gibbs sampler. Bayesian analyzes are often motivated as a means for incorporating prior beliefs, and are often criticized for the sensitivity to choice of prior distributions. In Hasbrouck (2009), the posterior density of the parameters in Roll's model is obtained by random draws based on their prior distribution and these random draws are generated using the Gibbs sampler. Hasbrouck (2009) restates Roll's model as

$$\begin{aligned} m_t &= m_{t-1} + u_t \\ u_t &\sim N(0, \sigma_u^2) \\ S_t &= m_t + cq_t \end{aligned} \tag{4}$$

where m_t is the efficient price (price in a frictionless market), following a Gaussian random walk, u_t is the public information shock and is assumed to be normally distributed with a mean of zero and a variance of σ_u^2 and independent of q_t, S_t is the log trade price, c is the effective cost, to be estimated, and q_t is the trade direction indicator, which equals +1 for a buy and -1 for a sell with equal probability.

The transaction price (S_t) are observed. The trade direction (q_t) and efficient price (m_t) are not. By taking first differences of the transaction price equation:

$$\Delta S_t = c\Delta q_t + u_t \tag{5}$$

Equation (5) is important for the Bayesian estimation approach because if the Δq_t were known, this would be a simple regression specification and the Bayesian approach would not have been warranted. The transaction price data sample is $S \equiv \{S_1, S_2, ..., S_T\}$, where T is the number of months in the time period. The model parameters $\{c, \sigma_u^2\}$, the latent buy/sell indicator, $q \equiv \{q_1, q_2, ..., q_T\}$, and the latent efficient prices, $m \equiv \{m_1, m_2, ..., m_T\}$ are to be numerically estimated.

The approach of the Gibbs sampler is an iterative process in which one sweep consists of three steps [7]. Each sampler is run for 1000 sweeps, of which the first 200 are discarded to remove the effect of starting values (burn-in values), and the mean value of c in the remaining 800 sweeps serves as the estimate of the effective cost. We use the program code provided on Hasbrouck's website to estimate the Gibbs measure empirically. Hasbrouck corrects for possible negative transaction cost estimates in the Roll (1984) model by restricting them to be positive in the Bayesian approach. For each currency, the standard deviation of the transaction cost prior is set to be equal to $\sqrt{\overline{a} - \overline{b}}$, where $\overline{a}$ and $\overline{b}$ are the daily averages of ask and bid prices respectively.

3.1.4 Menkhoff et al. (2012) Liquidity Measures

Menkhoff et al. (2012) propose a relative bid-ask spread and volatility measures to capture transaction cost. The bid-ask spread is the difference between the bid and ask (offer) prices quoted by a dealer who makes a market in FX market and bridges the time gaps between asynchronous public buy and sell orders. The ask (offer) price quoted for a security includes a premium for immediate buying, and the bid price reflects a price concession for immediate sale. The bid-ask spread may thus be viewed as the price the dealer (or market-maker) demands for providing liquidity services and immediacy of execution.

$$\text{Bid-Ask Spread} = \frac{A_t - B_t}{M_t} \tag{6}$$

$$Volatility = |(\Delta S_\tau)| \tag{7}$$

where A_t, B_t, and τ are the ask quote, bid quote, and return period respectively. M_t is the mid-quote price at time t. The volatility measure has similarities to measures of realized volatility used by Andersen, Bollerslev, Diebold, and Labys (2001), although we use absolute returns following Menkhoff et al. (2012), and not squared returns to minimize the impact of outlier returns.

3.1.5 Corwin-Schultz (2012) Liquidity Measure

Corwin and Schultz (2012) develop a spread estimator from daily high and low transaction prices. Daily high (low) prices are almost always buy (sell) orders. Hence the high-low ratio reflects both the asset's variance and its bid-ask spread. While the variance component of the high-low ratio is proportional to the

[7] First, a Bayesian regression is used to estimate the effective cost, c, based on the sample of prices, the starting values of q, and the priors for c, σ_u^2. Second, a new draw of σ_u^2 is made from an inverted gamma distribution based on S, q, the prior for σ_u^2, and the updated estimate of c. Third, new draws of q and m are made based on the updated estimate of c and the new draw of σ_u^2.

return interval, the spread component is not. This allows for a closed form derivation of the spread estimator as a function of high-low ratios over one-day and two-day intervals. The Corwin-Schultz spread estimator is given by:

$$
\begin{aligned}
\text{Corwin Schultz} &= \frac{2\left(e^{\alpha}-1\right)}{1+e^{\alpha}} \\
\alpha &= \left(1+\sqrt{2}\right)\left(\sqrt{\beta}-\sqrt{\gamma}\right) \\
\beta &= \sum_{j=0}^{1}\left[ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2 \\
\gamma &= \left[ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2
\end{aligned} \tag{8}
$$

where H and L are the high and low daily close prices respectively. Being a spread estimator, a lower value indicates high liquidity and vice versa.

3.1.6 Proportion of Zero Returns Liquidity Measure

Lesmond, Ogden, and Trzcinka (1999) suggest that stock liquidity can be measured by the proprotion of zero-return days, whose estimation requires only the time series of daily stock returns. The economic intuition behind this zero-return measure is that informed traders will trade only when the gain from their private information is large enough to offset the transaction cost. In other words, if the stock liquidity is low, the high transaction cost will deter the trading from informed traders and therefore prevent private information from being revealed. As a result, a larger proportion of zero-return days should be observed for illiquid stocks. Lee (2011) adopts the zero-return measure to examine the pricing of liquidity risk in global equity markets, and Liu (2006) uses a modified version to show that liquidity is an important source of priced risk in the equity market. In this study, we adopt the zero-return measure with currency returns and the same economic intuition holds. More specifically, the zero-return mesure (ZeroRet) is defined as follows:

$$
ZeroRet = \frac{\text{Number of days with zero returns in a month}}{\text{Total number of trading days in a month}} \tag{9}
$$

Daily liquidity measures are constructed for the ten currency-pairs using equations (1) to (9). Since each spread measure captures different dimension of liquidity, a principal component analysis (PCA) is used to extract the common liquidity information among the constructed measures across the ten currency-pairs. This is consistent with Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) in the equity literature. The first principal component represents the market-wide liquidity measure[8]. Currency-pair

[8]We extract the common systematic components of liquidity across ten currency-pairs and from a set of eight measures of liquidity. With ten currency-pairs (n=10), eight measures of liquidity, and a sample size of T (T=4326), we extract latent

liquidity measures are also constructed across the liquidity measures for the ten currency-pairs. Figure 1 in the Appendix shows the profile of the constructed liquidity measures. The profiles of the currency-pair liquidity measures and the eight liquidity measures for all currencies are shown in the Internet Appendix. It is evident that constructed liquidity measures capture the drop in market liquidity during the Lehman Brothers collapse in September 2008.

Tables 1 and 2 in the Appendix show the summary statistics of constructed liquidity measures for the whole sample and the financial crisis regime. Results of other regimes are available in the Internet Appendix. For the whole sample, JPY, GBP, EUR, and DKK appear to be the liquid currencies as they have the least spreads across all the eight liquidity measures. In contrast, NZD, AUD, NOK, CAD, and SEK appear to be the illiquid currencies as indicated by their wide spreads. There was a slight change in the crisis regime where EUR, DKK, and GBP were the most liquid currencies across the measures. NZD and AUD remain the most illiquid across the measures in the crisis regime. Tables 3 and 4 show the co-movement of constructed liquidity measures.

Roll (1984), Zero Return and Effective Spread measures are dropped from the measures because of their low correlation with the market-wide liquidity measure. The correlation structure in Tables 3 and 4 is the resulting matrix after the Roll (1984), Zero Return and Effective Spread measures are dropped and the market-wide liquidity measure reconstructed with the remaining measures. The market-wide liquidity measure (MKT) is therefore constructed using the five best liquidity measures across the ten currency-pairs in the sample. The correlation structure of the five best measures and the market-wide liquidity measure is shown in Table 4.

Although the bid-ask spread is perceived to be a good proxy of liquidity, this study shows that it is the least important among the best five measures. This may be due to the fact that bid-ask spread is only good for capturing liquidity of small trade size. Bao et al. (2011) show that the illiquidity in corporate bonds is significantly greater than what can be explained by bid-ask spreads. The correlation of the currency-pair liqudity measures and the systematic market-wide liquidity is shown in the Internet Appendix.

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factors from a cross-sectional sample of T x M (M=10 x 8 = 80). The first principal component represents the market-wide liquidity measure. Following Korajczyk and Sadka (2008), we demean, standardize, and collect all eight liquidity measures in a 8 x T matrix, L_j, for each currency-pair, j. T is the number of days in our sample. We use the eigenvector decomposition of the covariance matrix, $L_j L_j^T E_j = E_j D_j$, where E_j is the 8 x 8 eigenvector matrix and D_j the 8 x 8 diagonal matrix of eigenvalues, and ^{T} is the transpose operator. The first principal component of currency-pair, j, is given by $E_j^T L_j$ corresponding to the largest eigenvalue, where E_j is chosen so that the variance of $E_j^T L_j$ is maximized over all vectors of E_j. PCA assumes that principal components with large variances have important dynamics and lower variances correspond to noise.

Overall, summary statistics show that JPY, EUR, DKK and GBP are the most liquid currencies in the sample. In contrast, NZD, AUD, NOK and SEK are the most illiquid. Estimating the specification of equation (10) in the next section, liquidity betas indicate that JPY is the most liquid currency in the whole sample period followed by EUR. This is in line with the perception of market participants and the fact that the Euro and Japanese yen have by far dominated the FX market in terms of market share and turnover (BIS, 2013). Following Pastor and Stambaugh (2003), liquidity beta is the loading on the market-wide liquidity measure when individual currencies are regressed on the market-wide liquidity measure. Highly liquid currencies are expected to have smaller loading because they are not that sensitive to the market-wide liquidity measure. In contrast, illiquid currencies are expected to have higher loadings because they are sensitive to the market-wide liquidity measure.

4 Currency-pair Liquidity Sensitivity to Systematic FX Liquidity

Following Pastor and Stambaugh (2003) and Mancini et al. (2013), we analyze the sensitivity of the liquidity of exchange rate j to a change in the systematic or market-wide liquidity measure. We run a time-series regression of individual liquidity, $L_{j,t}$ on common liquidity measure $L_{M,t}$ by estimating the following equation:

$$L_{j,t} = \alpha_j + \beta_j L_{M,t} + \varepsilon_{j,t} \tag{10}$$

where $\varepsilon_{j,t}$ represents an idiosyncratic liquidity shock. The sensitivity is captured by the slope coefficient β_j. To prevent potentially upward-biased sensitivities, we reconstruct $L_{M,t}$ excluding exchange rate j. Estimation results in Tables 5 and 6 (Appendix) indicate that specification of equation (10) provides a good fit to the data with an R^2 ranging from 54.2% to 85.6%. All estimated slope coefficients are positive and statistically significant at all conventional levels. This provides the evidence that the liquidity of every FX rate depends positively on the market-wide liquidity measure. The most liquid currencies (JPY, EUR, DKK, and CHF) have the lowest liquidity sensitivities to market-wide FX liquidity. The least liquid currencies (SEK, NOK, AUD, and NZD) have the highest liquidity sensitivities.

These findings suggest that illiquid currencies are very sensitive to changes in market-wide liquidity. In contrast, the most liquid currencies are less sensitive to changes in market-wide liquidity and as a result, may offer a "liquidity hedge" as they tend to remain relatively liquid, even when the market-wide liquidity drops. These findings are consistent with Mancini et al. (2013) and Brunnermeier et al. (2008). Liquidity betas of equation (10) are then used to rank all the ten currencies in our sample in order of decreasing market liquidity (JPY, EUR, DKK, CHF, CAD, GBP, NZD, AUD, NOK, SEK).

4.1 Carry Trade Returns

We denote the carry trade return in the foreign currency investment financed by borrowing in the domestic currency (USD$) by

$$r^e_{j,t+1} = \left(i^*_{j,t} - i_t\right) - \Delta s_{j,t+1} \tag{11}$$

where $r^e_{j,t+1}$ is the excess carry trade returns over UIP, $s_t = log(\text{nominal exchange rate})$, $i^*_{j,t}$ and i_t are the logarithm of foreign interest rate for currency j and domestic (U.S.) interest rate respectively, and $\Delta s_{t+1} \equiv s_{t+1} - s_t$, is the depreciation of the foreign currency. Under UIP, r^e_{t+1} should not be forecastable, that is, $E_t\left[r^e_{j,t+1}\right] = 0$. Hence, r^e_{t+1} can be interpreted as the abnormal return to a carry trade strategy where the foreign currency is the investment currency and the U.S. dollar is the funding currency.

Summary statistics of carry trade returns in Tables 7 and 8 indicate that financial crisis regime exhibit higher negative returns. This could be due to carry traders unwinding their positions when liquidity dries up during financial crisis. This finding is consistent with Brunnermeier et al. (2008). Post-crisis regime is marked by high carry trade returns as indicated by their Sharpe ratios[9]. This implies that carry trade investors engage in this risky speculative trade with the expectation that the high interest rate currency will continue to appreciate in "calmer regimes" where liquidity picks up.

4.2 Two-Factor Liquidity-Adjusted Model

Breeden (1979) shows that mimicking portfolios can replace the state variables in the intertemporal asset pricing model of Merton (1973). A number of studies use mimicking portfolios for economic factors. Chen, Roll, and Ross (1986) construct mimicking portfolios for several macroeconomic factors. Breeden, Gibbons, and Litzenberger (1989) adopt mimicking factors for aggregate consumption growth, and Fama and French (1996) construct their SMB and HML mimicking portfolios in an attempt to capture distress risk. The construction of our mimicking liquidity factor, IML, is discussed in the next section.

[9]Summary statistics available in the Internet Appendix

Both the arbitrage pricing theory (APT) and equilibrium models show that asset pricing models have the following form:[10]

$$E(r_j) = \lambda_0 + \beta_{j1}\lambda_1 + \beta_{j2}\lambda_2 + ... + \beta_{jK}\lambda_K \tag{12}$$

where $E(r_j)$ is the expected return of asset j, β_{jk} is the beta of asset j relative to the kth risk factor, λ_k is the risk premium of the kth factor (k=1, 2, ..., K), and λ_0 is the expected zero-beta rate. We construct our two-factor model based on the CAPM plus the IML factor that captures liqudity risk. The expected excess return of security/portfolio j from the two-factor model is:

$$E(r_j) - r_f = \beta_{m,j}\left[E(r_m) - r_f\right] + \beta_{l,j}E(IML) \tag{13}$$

where $E(r_m)$ is the expected return of the market portfolio, $E(IML)$ is the expected return of the mimicking liquidity factor, and the factor loadings $\beta_{m,j}$ and $\beta_{l,j}$ are the slopes in the time-series regression:

$$r^e_{j,t} = \alpha_j + \beta_{m,j}AER_t + \beta_{l,j}IML_t + \varepsilon_{j,t} \tag{14}$$

$r_{j,t}$ is the excess carry trade returns and AER_t is a proxy of the market risk factor of the G10 currencies. AER_t in a currency setting is equivalent to $[E(r_m) - r_f)]$ in equation (13). α_j captures any abnormal return that is not explained by the FX risk factor.

The two-factor model implies that the expected excess carry trade returns of a currency is explained by the covariance of its return with the market factor and the liquidity factor. If the two-factor model explains asset returns, the intercept α_j should not be significantly different from zero. Equation (14) is valid only if the liquidity factor is a priced state variable.

4.3 Liquidity Risk Factor

We formally test whether liquidity risk affects carry trade returns. To do this, we assume that the variation in the cross-section of returns is caused by different exposures of risk factors as documented by Ross (1976) in his APT model. We introduce a liquidity risk factor given by a currency portfolio that is long in the most illiquid and short in the most liquid FX rate on each day. We repeat this portfolio formation for two to five currency-pairs in our sample. For example, in the four currency portfolio formation, we utilized the

[10] The arbitrage pricing theory is developed by Ross (1976) and the multiple-beta equilibrium model by Merton (1973), Breeden (1979), and Cox, Ingersoll, and Ross (1985). Fama and French (1996) explore the relation between expected return and multiple risk factors.

regression loadings in equation (10) to go long in NZD, AUD, NOK, and SEK, and short in the most liquid four currencies (JPY, EUR, DKK, and CHF). Regression results with these portfolio formation are shown in the Internet Appendix. Following Chan, Karceski, and Lakonishok (1998), the portfolio that goes long in the most four illiquid currencies and short in the most four liquid currencies has the largest return volatility. This implies that the portfolio captures the highest amount of factor risk as measured by the volatility of the spread in returns between the long and short positions. We label this mimicking liquidity portfolio as IML, which stands for illiquid minus liquid portfolio. IML is interpreted as the return in dollars on a zero-cost trading strategy that goes long in illiquid currencies and short in liquid currencies. As IML is a tradable risk factor, currency investors can easily hedge associated liquidity risk exposures.

Lustig et al. (2011) introduce HML as a carry trade risk factor. HML is given by a currency portfolio that is long in high interest rate currencies and short in low interest rate currencies. Lustig et al. (2011) find that HML explains the common variation in carry trade returns and suggest that this risk factor captures "global risk" for which carry traders earn a risk premium. Following Lustig et al. (2011) in the spirit of arbitrage pricing theory and equilibrium models, we run a 2-factor model with IML as currency portfolio liquidity risk factor and AER as the market risk factor. The "market risk" factor or average excess return (AER) is computed as the score of the first principal component of all the ten currency-pair carry trade returns. AER is interpreted as the average return for a U.S. currency investor who goes long in all the ten exchange rates available in the sample. The following factor model from equation (14) is then estimated:

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{IML,j} IML_t + \varepsilon_{j,t} \tag{15}$$

where $\beta_{AER,j}$ and $\beta_{IML,j}$ represent the exposure of carry trade return j to the market risk factor and liquidity risk factor respectively. As dictated by econometric modeling, any unusual or abnormal return that is not explained by the FX risk factor is captured by the constant α_j.

As shown in Tables 9 to 12, equation (15) provides a good fit to the data with adjusted-R^2 for regressions ranging from 41% to 93%. This implies that the vast majority of monthly variation in carry trade returns during any exchange rate regime can be explained by two risk factors (the market risk factor and the liquidity risk factor). Liquidity betas, β_{IML_j}, are economically and statistically significant at all conventional levels. As shown in Table 19, economic significance of liquidity betas implies that when liquidity factor (IML) decreases by one standard deviation, AUD depreciates by 0.39 standard deviations, whereas JPY appreciates by 0.62 standard deviations for the whole sample. The consistency of results across regimes implies that carry trade returns are not driven by financial crisis or disaster events in the economy.

When we run a univariate regresion with IML as the only explanatory factor, adjusted-R^2 as high as 61.3% is obtained as shown in the Internet Appendix. This underscores the crucial role of liquidity risk in explaining the variation of carry trade returns across exchange rate regimes. As noted by Lustig et al. (2011), all exchange rates load fairly equally on the market risk factor (AER), which helps in explaining the average level of carry trade returns. Liquidity betas, β_{IML_j}, however, vary significantly across currencies and exchange rate regimes.

An interesting pattern emerges from the results. Typical high interest rate currencies, such as AUD and NZD, exhibit the largest positive liquidity betas and typical low interest rate currencies, such as JPY and CHF, exhibit the largest negative liquidity betas. Figure 2 in Appendix shows the liquidity betas corresponding to low and high interest rate currencies. This implies that high interest rate currencies are sensitive to liquidity risk and provide a higher exposure to liquidity risk. In contrast, low interest bearing currencies are less sensitive to liquidity risk and thus offer insurance against liquidity risk or exhibit a "liquidity hedge" against liquidity risk. The high interest rate currencies correspond to the illiquid FX rates whereas the low interest rate currencies are the liquid FX rates in our sample. These findings indicate that when FX liquidity improves, illiquid currencies appreciate further because of the positive liquidity betas. In contrast, liquid currencies depreciate when liquidity improves because of the negative liquidity betas[11]. This observation consistent with the findings of Mancini et al. (2013), increases the deviation of FX rates from UIP (Forward Premium Puzzle).

FX liquidity is given by liquidity level and liquidity shocks. The liquidity level is the systematic market-wide liquidity measure. Following Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), liquidity shock is defined as the residuals from an AR(1) model fitted to the systematic market-wide liquidity measure. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) show that correlations between liquidity shocks and returns are closer to twice the correlations between liquidity levels and returns. Correlation results in the Internet Appendix shows that this is consistent with carry trade returns. Such strong comovements between carry trade returns and shocks in liquidity are consistent with liquidity risk being a risk factor for carry trade returns. When the hedged liquidity factor, IML, is replaced with the innovations factor (liquidity shocks), the results in Tables 15 to 18 are virtually in the same direction as in Tables 9 to 12. The implication of this finding is that, irrespective of the method used to construct the FX liquidity risk factor, both liquid and illiquid currencies will retain their characteristics and dynamics toward the risk factor. This demonstrates the importance of liquidity risk as a determinant of carry trade returns.

[11] Results are consistent across all exchange rate regimes (pre-crisis and post-crisis).

4.4 FX liquidity risk premium

After showing that FX mimicking liquidity portfolios explain currency excess returns, we investigate whether systematic liquidity risk is priced in the cross-section of FX excess returns of the sorted portfolios. The question that we ask is, how much liquidity premium does currency investors require to hold portfolios made up of the G10 currencies?

We answer the above question by quantifying the FX liquidity risk premium in the FX market. We do this by conducting a standard Fama and MacBeth (1973) regression analysis. In the first step, we run a time-series regression of excess returns on the factors. In the second step, we run a cross-sectional regression of average excess returns on the betas. Following Lustig et al. (2011), we do not include a constant in the second step ($\lambda_0 = 0$). We test whether our liquidity risk factor prices the excess returns of the liquidity-sorted portfolios. We do this by testing the significance of the liquidity risk factor conditioning on other factors such as the global carry trade risk factor proposed by Lustig et al. (2011).

We apply the standard Fama-MacBeth procedure by estimating the sensitivities of the mimicking portfolios to the liquidity risk factor and some common currency risk factors through a time-series regression of the form shown in equation (16). The choice of our common currency risk factor is the carry risk factor (HML) proposed by Lustig et al. (2011) or the average excess carry returns (AER).

$$\bar{r}^e_{j,t} = \beta_j^{LIQ} IML_t^{LIQ} + \beta_j^{Other} f_t^{Other} + \varepsilon_{j,t} \qquad \text{for j=1, ...,4} \tag{16}$$

We determine the cross-sectional impact of the sensitivities on the FX portfolio's excess returns by running a cross-sectional regression of the excess returns on the sensitivities at each point in time as shown in equation (17).

$$\bar{r}^e_{j,t} = \beta_j^{LIQ} \lambda_t^{LIQ} + \beta_j^{Other} \lambda_t^{Other} + \varepsilon_{j,t} \qquad \text{for t=1, ...,T} \tag{17}$$

where λ_t is the market price of a specific risk factor at time t and the $\beta's$ are calculated from the first-stage regression in equation (16). The market price of risk and pricing errors are estimated as shown in equations (18) to (20).

$$\hat{\lambda}^{LIQ} = \frac{1}{T} \sum_{t=1}^{T} \lambda_t^{LIQ} \tag{18}$$

$$\hat{\lambda}^{Other} = \frac{1}{T}\sum_{t=1}^{T}\lambda_t^{Other} \tag{19}$$

$$\hat{\varepsilon}_j = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_{j,t} \tag{20}$$

To show that the liquidity risk is priced in the cross-section of currency excess returns in the FX market, the market price must be positive and statistically significant. In addition, the market price must stay significant after controlling for other common currency factors (Lustig et al., 2011). Table (21) shows the results of the Fama-MacBeth procedure with different regression specifications. Panel A reports the analysis where we test whether the systematic liquidity risk factor is priced in the cross-section of currency excess returns. The market price of risk, λ coefficient associated with the systematic liquidity risk is positive and statistically significant. We estimate an annualized liquidity risk premium of about 4.12 percent. Controlling for other common risk factors, Panels B and C show the results when the dollar risk factor and average excess returns are included in our specification. In both panels, the λ associated with the systematic liquidity risk remains statistically significant at all conventional levels.

In Panel C, our results show that the carry risk factor is not statistically significant in explaining the cross-sectional variation of currency excess returns. We therefore validate the hypothesis that liquidity risk is a priced factor in the FX market. Mancini et al. (2013) suggest that currency investors demand a liquidity risk premium by examining the persistence of the shocks to market-wide liquidity and showing that the shocks are correlated with carry trade returns. We validate this observation in Tables (15) to (18). Banti, Phylaktis, and Sarno (2012) estimate a liquidity risk premium of about 4.7 percent per annum. Our lower estimate of the liquidity risk premium can be explained by our sample of G10 currencies as compared to their sample inclusion of currencies from developing countries, which are perceived to be illiquid in comparison with the G10 currencies.

4.5 Robustness Checks

As a robustness check, we use equation (15) to explain the variation of carry trade index returns, using the Deutsche Bank's G10 DB PowerShares Currency Harvest (DBV) Index fund. Table 20 in the Appendix shows the results of how our liquidity risk factors explain carry trade index returns. Equation (15) is estimated replacing excess carry trade returns with the excess DBV returns. The Internet Appendix shows other results of the impact of the mimicking liquidity risk factor, market-wide liquidity level, and the innovations liquidity risk factor[12]. The liquidity beta for DBV is significant at all conventional levels. This supports the finding that liquidity risk is an important risk factor for currency carry trade returns across all exchange rate regimes.

Following Lustig et al. (2011) and Mancini et al. (2013), we regress FX returns ($-\Delta S_{j,t+1}$) on the market and liquidity risk factors. All liquidity betas are virtually the same as shown in the Internet Appendix. This implies that liquid currencies act as a liquidity hedge because they appreciate when market-wide FX liquidity drops, not because the interest rates on these currencies increase. In contrast, illiquid currencies have high exposure to liquidity risk because they depreciate when FX liquidity drops, not because the interest rates associated with these currencies decline. The support of the robustness checks to the findings of this study confirms that liquidity risk is an important risk factor for carry trade returns across all exchange rate regimes.

5 Conclusion

Using daily low-frequency liquidity measures, we provide a comprehensive investigation into FX liquidity risk and carry trade returns. The paper's main contribution is the identification of a low-frequency systematic liquidity risk measure, which significantly explains the cross-sectional variation of currency excess returns. We show that FX liquidity is an important issue in the FX market. Liquidity betas are used to construct liquidity risk factors, which help in explaining the variation of carry trade returns across exchange rate regimes. We inferred from our analyses that carry trade investors demand premiums for holding illiquid currencies in their portfolios, implying that liquidity risk is priced. We employ a standard asset pricing approach and introduce a measure of mimicking FX liquidity portfolio as a systematic risk factor. We estimate the liquidity risk premium to be around 4.12 percent per annum, which is both statistically and economically significant.

The implication of this finding is two fold. Monitoring FX liquidity will enable central banks and regulatory authorities to evaluate the effectiveness of their policies. The role of liquidity risk will help currency investors to adequately assess the risk of their international portfolios and carry trade investors would be able to assess currency crashes better due to liquidity spirals. In the area of portfolio selection and diversification, our finding may guide investors in balancing expected liquidity risk against expected carry trade returns.

[12] Results available in Internet Appendix

Bank holding companies (BHCs) in the United States are required by bank regulators to estimate and validate their “risk not in model (RNiM)”. Most risk organizations in BHCs are yet to fully satisfy RNiM requirement by the regulators. Most capital markets risk models capture market risk, counterparty credit risk (CCR), potential future exposure (PFE), but not “risk not in model (RNiM)”. Not properly capturing RNiM could bias P&L attribution at the Top of the House (TOH) reporting. Liquidity risk with our constructed low-frequency measure could be a good starting point of capturing RNiM. In sum, we demonstrate the importance of liquidity risk as a determinant of carry trade returns.

Further research will be aimed at improving the accuracy of the low frequency liquidity measures, especially the Roll estimator and the effects of order flow on volatility and carry trade returns. It would also be interesting to perform similar analyses using emerging currencies to evaluate how important FX liquidity risk could be used in explaining the cross-section of these emerging market currencies.

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6 Appendix

Table 1: Summary Statistics of Liquidity Measures (Whole Sample: Jan 1999 - Jul 2015)

	EUR	**GBP**	**JPY**	**CAD**	**CHF**	**AUD**	**NZD**	**NOK**	**SEK**	**DKK**
					Roll (1984) Spread (%)					
Mean	0.49	0.39	0.47	0.43	0.54	0.58	0.60	0.56	0.56	0.49
Std. Dev	0.26	0.20	0.27	0.28	0.30	0.44	0.37	0.29	0.32	0.27
					Modified Roll - Goyenko et al., 2009 (%)					
Mean	0.39	0.34	0.33	0.32	0.42	0.46	0.50	0.45	0.47	0.39
Std. Dev	0.18	0.16	0.18	0.24	0.20	0.28	0.22	0.22	0.24	0.18
					Gibbs Spread - Hasbrouck, 2009 (%)					
Mean	0.85	0.74	0.72	1.06	0.95	1.03	1.10	1.02	1.03	0.86
Std. Dev	0.29	0.27	0.35	0.33	0.54	0.55	0.43	0.39	0.39	0.29
					Volatility - Menkhoff et al., 2012 (%)					
Mean	1.66	1.43	1.42	1.65	1.78	2.00	2.14	1.98	2.00	1.66
Std. Dev	0.56	0.53	0.69	0.72	0.65	1.05	0.87	0.75	0.78	0.57
					Corwin-Schultz 2012 (bps)					
Mean	24.86	21.82	21.93	25.10	27.94	29.80	32.96	30.24	30.60	23.90
Std. Dev	9.26	9.55	10.13	11.99	11.40	13.71	13.59	14.80	14.93	10.92
					Bid-Ask Spread - Menkhoff et al., 2012 (bps)					
Mean	2.78	2.81	12.64	3.83	4.58	5.71	10.39	10.70	8.80	4.67
Std. Dev	2.07	1.54	23.64	2.27	2.33	2.59	4.02	6.34	4.43	9.76
					Proportion of Zero Returns - LOT, 1999 (%)					
Mean	0.66	0.50	5.83	1.00	1.01	0.89	0.96	4.27	4.53	5.48
Std. Dev	1.66	1.64	5.34	2.15	2.12	2.13	2.35	4.70	4.84	5.24
					Effective Spread - Goyenko et al., 2009 (bps)					
Mean	0.20	0.19	2.63	0.44	0.35	0.76	0.84	2.14	2.21	1.78
Std. Dev	0.17	0.11	0.84	0.47	0.17	0.53	0.63	1.49	0.92	0.77

Table 2: Summary Statistics of Liquidity Measures (Crisis: Jan 2007 - Dec 2009)

	EUR	**GBP**	**JPY**	**CAD**	**CHF**	**AUD**	**NZD**	**NOK**	**SEK**	**DKK**
					Roll (1984) Spread (%)					
Mean	0.48	0.44	0.64	0.65	0.60	0.88	0.86	0.71	0.67	0.48
Std. Dev	0.24	0.22	0.40	0.41	0.33	0.74	0.51	0.36	0.42	0.23
					Modified Roll - Goyenko et al., 2009 (%)					
Mean	0.44	0.43	0.50	0.39	0.45	0.65	0.67	0.59	0.61	0.44
Std. Dev	0.29	0.27	0.27	0.26	0.22	0.54	0.35	0.34	0.43	0.29
					Gibbs Spread (%)					
Mean	0.90	0.96	1.09	1.24	0.98	1.47	1.50	1.32	1.29	0.90
Std. Dev	0.42	0.46	0.50	0.46	0.39	1.02	0.68	0.64	0.68	0.42
					Volatility - Menkhoff et al., 2012 (%)					
Mean	1.75	1.85	2.17	2.05	1.89	2.90	2.98	2.54	2.54	1.75
Std. Dev	0.82	0.90	1.05	1.00	0.73	1.94	1.40	1.22	1.32	0.81
					Corwin-Schultz 2012 (bps)					
Mean	27.26	29.07	32.93	31.97	31.29	42.29	45.50	39.74	36.93	26.64
Std. Dev	13.22	15.34	14.31	13.80	12.37	23.11	20.16	21.97	19.63	12.61
					Bid-Ask Spread - Menkhoff et al., 2012 (bps)					
Mean	2.48	3.27	6.19	5.19	6.71	5.94	10.09	15.52	13.37	3.68
Std. Dev	1.22	1.48	2.43	3.21	3.58	3.02	4.96	6.71	6.48	1.61
					Proportion of Zero Returns - LOT, 1999 (%)					
Mean	0.49	0.24	5.21	1.02	0.74	0.26	1.01	2.93	2.92	4.68
Std. Dev	1.42	1.45	8.74	1.94	1.68	1.08	2.18	3.64	3.78	4.22
					Effective Spread - Goyenko et al., 2009 (bps)					
Mean	0.09	0.09	2.55	0.28	0.30	0.48	0.52	1.57	1.73	1.24
Std. Dev	0.06	0.04	0.80	0.10	0.08	0.14	0.16	0.54	0.49	0.36

Summary statistics of pre-crisis and post-crisis are available in the Internet Appendix

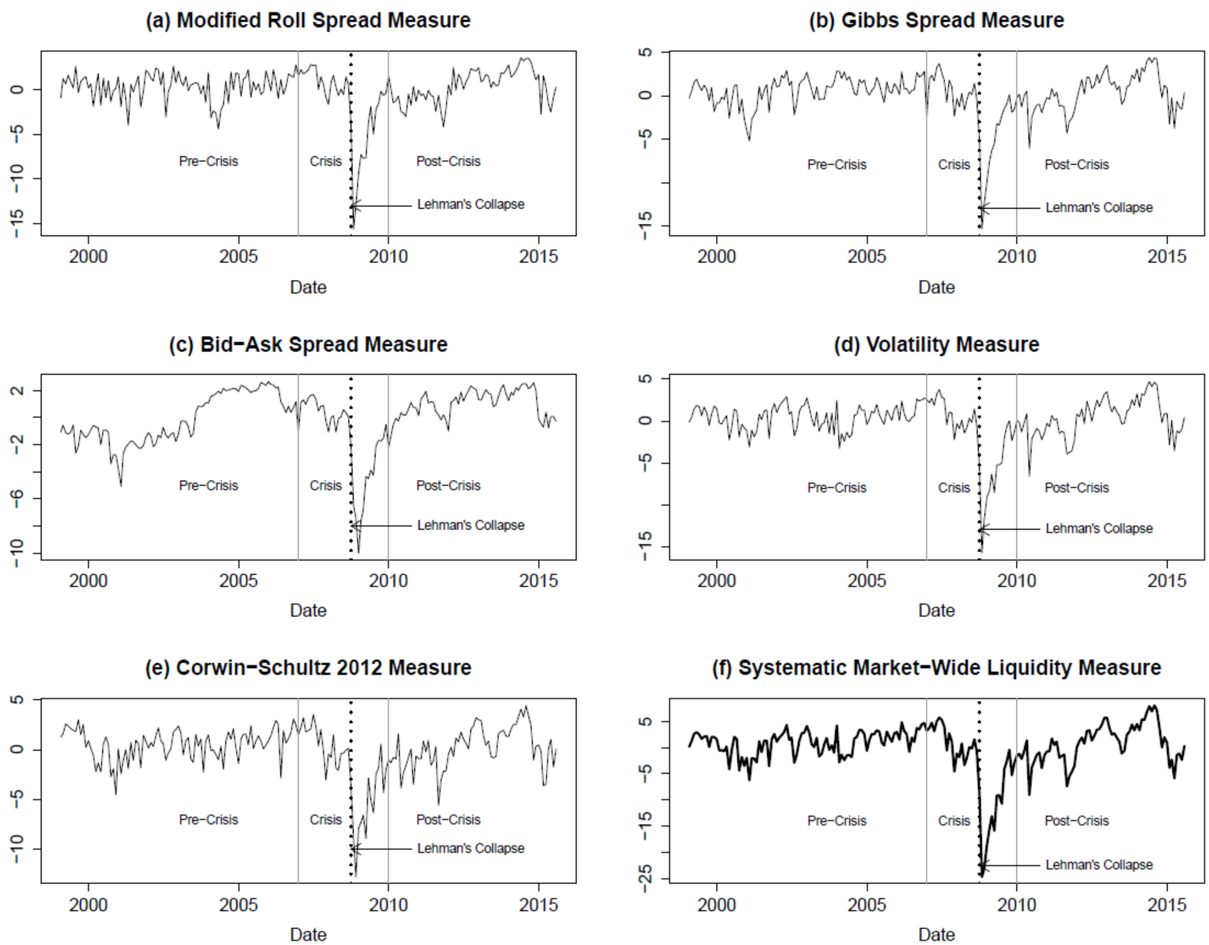

Figure 1: Best 5 and Systematic Market-Wide Liquidity Measures: Modified Roll, Gibbs, Bid-Ask Spread, Volatility, Corwin-Schultz 2012, and Systematic Market-Wide Liquidity.

Panels (a) to (e) depict monthly standardized liquidity measures across all ten currencies. Each measure is the score of the first principal component across all currencies. The sign of each liquidity measure is adjusted to represent liquidity instead of illiquidity. Panel (f) shows the profile of the systematic market-wide liquidity measure. The systematic market-wide liquidity measure is the first principal component obtained by running a PCA of the best 5 measures across the ten currency-pairs. Sample period is from January 1999 to July 2015. Gray dotted line represents Lehman Brothers collapse in September 2008.

Table 3: Correlation of Liquidity Measures

	Roll	GHT	Gibbs	Vol	BAS	CS	ZeroRet	ES	MKT
Roll	1								
GHT	0.46	1							
Gibbs	0.69	0.82	1						
Vol	0.72	0.91	0.91	1					
BAS	0.45	0.59	0.70	0.62	1				
CS	0.74	0.77	0.84	0.87	0.64	1			
ZeroRet	0.30	0.37	0.32	0.43	0.08	0.38	1		
ES	-0.02	0.02	0.04	0.04	-0.35	0.06	0.25	1	
MKT	0.72	0.91	0.95	0.97	0.75	0.92	0.37	-0.02	1

Roll, GHT, Gibbs, Vol, BAS, CS, ZeroRet, ES, and MKT denote Roll 1984 Measure, modified Roll 1984 by Goyenko et al. (2009), Gibbs by Hasbrouck (2009), Volatility, Bid-Ask Spread, Corwin-Schultz 2012, Proportion of Zero Returns, Effective Spread, and Systematic Market-Wide Liquidity respectively.

Table 4: Correlation of Best Five (5) Liquidity Measures

	GHT	Gibbs	Vol	CS	BAS	MKT
GHT	1					
Gibbs	0.82	1				
Vol	0.91	0.91	1			
CS	0.77	0.84	0.87	1		
BAS	0.59	0.70	0.62	0.64	1	
MKT	**0.91**	**0.95**	**0.97**	**0.92**	**0.75**	**1**

GHT, Gibbs, Vol, BAS, CS, and MKT denote Goyenko et al. (2009), Gibbs, Volatility, Bid-Ask Spread, Corwin-Schultz 2012, and Systematic Market-Wide Liquidity respectively.

Table 5: Liquidity Sensitivity to Changes in Market-Wide FX Liquidity for EUR, GBP, CAD, JPY, and CHF (Whole Sample: Jan 1999 - Jul 2015).

This table reports liquidity sensitivities to changes in the market-wide liquidity measure as shown in equation (10):

$$L_{j,t} = \alpha_j + \beta_j L_{M,t} + \varepsilon_{j,t}$$

Liquidity of FX rate j is excluded before computing $L_{M,t}$. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. N is the number of observations. The sample is from January 1999 to July 2015.

	Dependent variable:				
	EUR.PC1	GBP.PC1	CAD.PC1	JPY.PC1	CHF.PC1
	(1)	(2)	(3)	(4)	(5)
MKT	0.314^{***}	0.341^{***}	0.327^{***}	0.239^{***}	0.321^{***}
	(0.037)	(0.016)	(0.020)	(0.033)	(0.036)
Constant	0.028	−0.015	−0.053	−0.023	0.045
	(0.139)	(0.065)	(0.084)	(0.170)	(0.091)
Observations	199	199	199	199	199
R^2	0.751	0.856	0.705	0.542	0.585
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: Liquidity Sensitivity to Changes in Market-Wide FX Liquidity for AUD, NZD, and NOK, SEK, and DKK (Whole Sample: Jan 1999 - Jul 2015).

	Dependent variable:				
	AUD.PC1	NZD.PC1	NOK.PC1	SEK.PC1	DKK.PC1
	(1)	(2)	(3)	(4)	(5)
MKT	0.435^{***}	0.434^{***}	0.437^{***}	0.450^{***}	0.315^{***}
	(0.037)	(0.018)	(0.012)	(0.022)	(0.038)
Constant	−0.025	0.033	−0.024	−0.038	−0.055
	(0.067)	(0.055)	(0.086)	(0.073)	(0.121)
Observations	199	199	199	199	199
R^2	0.828	0.834	0.802	0.854	0.755
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Summary Statistics of Carry Trade Returns (Whole Sample)

	EUR	**GBP**	**CAD**	**JPY**	**CHF**	**AUD**	**NZD**	**NOK**	**SEK**	**DKK**
Panel A: Whole Sample (Jan 1999 - Jul 2015, N=199)										
FX return: $\Delta S_{j,t+1}$										
Mean	-0.40	-0.37	-0.12	-0.51	2.13	1.09	1.32	-0.48	-0.38	-0.40
Std. Dev.	10.52	8.57	8.29	9.61	10.85	13.14	13.55	11.54	11.74	10.48
Interest rate differential: $i_t^f - i_t^d$										
Mean	-0.15	0.89	0.29	-2.11	-1.36	2.47	2.78	1.39	0.10	-0.01
Std. Dev.	1.28	1.09	0.81	2.09	1.42	1.59	1.51	1.85	1.68	1.36
Carry trade returns: $r_{j,t+1}^e$										
Mean	0.24	1.26	0.41	-1.63	-3.50	1.37	1.44	1.89	0.47	0.39
Std. Dev.	10.49	8.59	8.30	9.65	10.83	13.14	13.56	11.55	11.71	10.45
SR	0.02	0.15	0.05	-0.17	-0.32	0.10	0.11	0.16	0.04	0.04

Table 8: Summary Statistics of Carry Trade Returns (Crisis)

	EUR	**GBP**	**CAD**	**JPY**	**CHF**	**AUD**	**NZD**	**NOK**	**SEK**	**DKK**
Panel B: Crisis (Jan 2007 - Dec 2009, N=36)										
FX return: $\Delta S_{j,t+1}$										
Mean	2.72	-6.39	3.42	8.24	5.53	4.32	0.88	2.44	-1.47	2.78
Std. Dev.	12.95	11.22	14.20	11.28	12.61	18.68	18.65	13.24	15.14	12.93
Interest rate differential: $i_t^f - i_t^d$										
Mean	0.26	1.12	-0.06	-2.23	-1.21	2.80	3.63	1.36	0.08	0.67
Std. Dev.	1.18	1.03	0.64	1.90	1.26	1.33	1.40	1.60	1.44	1.57
Carry trade returns: $r_{j,t+1}^e$										
Mean	-2.52	7.50	-3.51	-10.59	-6.83	-1.60	2.74	-1.17	1.49	-2.17
Std. Dev.	13.02	11.33	14.21	11.37	12.66	18.81	18.84	13.42	15.21	12.94
SR	-0.19	0.66	-0.25	-0.93	-0.54	-0.09	0.15	-0.09	0.10	-0.17

Summary statistics of pre-crisis and post-crisis are available in the Internet Appendix.

Table 9: Carry Trade Returns Regression Results (Whole Sample: Jan 1999 - Jul 2015)

This table reports time-series regression results for the monthly factor model in equation (15):

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{IML,j} IML_t + \varepsilon_{j,t}$$

$\beta_{AER,j}$ is the factor loading of the market risk factor defined as the score of the first principal component of all the ten currencies. The market risk factor is interpreted as the average excess FX rate of return for a U.S. investor who goes long in all the currencies. $\beta_{IML,j}$ is the factor loading of the liquidity risk factor, IML. IML is interpreted as the excess return of a portfolio that is long in the most four illiquid and short in the most four liquid exchange rates. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2 and N is the number of observations.

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.233***	0.723***	0.576***	0.650***	1.238***	1.032***	1.034***	1.096***	1.188***	1.229***
	(0.037)	(0.093)	(0.055)	(0.075)	(0.057)	(0.064)	(0.072)	(0.077)	(0.046)	(0.037)
IML	−0.089***	0.002	0.123***	−0.215***	−0.169***	0.186***	0.180***	0.040**	0.032**	−0.089***
	(0.013)	(0.034)	(0.016)	(0.024)	(0.018)	(0.023)	(0.022)	(0.019)	(0.015)	(0.012)
Constant	0.945	1.152	−1.946	0.372	−1.019	−0.560	−0.428	1.366	0.018	1.099
	(0.818)	(1.228)	(1.270)	(1.772)	(1.043)	(0.982)	(1.501)	(1.346)	(1.132)	(0.814)
Observations	199	199	199	199	199	199	199	199	199	199
R^2	0.891	0.542	0.599	0.407	0.800	0.858	0.791	0.762	0.844	0.892
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 10: Carry Trade Returns Regression Results (Pre-Crisis: Jan 1999 - Dec 2006)

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.208***	0.803***	0.451***	0.748***	1.207***	0.951***	1.019***	1.145***	1.258***	1.211***
	(0.046)	(0.059)	(0.077)	(0.120)	(0.049)	(0.069)	(0.087)	(0.078)	(0.063)	(0.044)
IML	−0.108***	−0.052*	0.099***	−0.153***	−0.155***	0.250***	0.239***	0.028	0.015	−0.107***
	(0.014)	(0.029)	(0.022)	(0.031)	(0.014)	(0.021)	(0.027)	(0.021)	(0.027)	(0.013)
Constant	0.958	1.030	−2.818	−0.712	−0.551	−0.540	−0.005	1.398	0.042	1.200
	(0.955)	(1.547)	(1.909)	(2.551)	(1.055)	(1.601)	(2.034)	(2.008)	(1.652)	(0.949)
Observations	96	96	96	96	96	96	96	96	96	96
R^2	0.911	0.588	0.663	0.419	0.893	0.809	0.748	0.697	0.811	0.913
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 11: Carry Trade Returns Regression Results (Crisis: Jan 2007 - Dec 2009)

This table reports time-series regression results for the monthly factor model in equation (15):

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{IML,j} IML_t + \varepsilon_{j,t}$$

$\beta_{AER,j}$ is the factor loading of the market risk factor defined as the score of the first principal component of all the ten currencies. The market risk factor is interpreted as the average excess FX rate of return for a U.S. investor who goes long in all the currencies. $\beta_{IML,j}$ is the factor loading of the liquidity risk factor, IML. IML is interpreted as the excess return of a portfolio that is long in the most four illiquid and short in the most four liquid exchange rates. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2 and N is the number of observations.

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.253***	0.478**	0.674***	0.666***	1.255***	1.295***	1.212***	0.759***	1.159***	1.250***
	(0.092)	(0.233)	(0.128)	(0.175)	(0.132)	(0.133)	(0.183)	(0.159)	(0.105)	(0.092)
IML	−0.087***	0.090*	0.119***	−0.252***	−0.176***	0.117***	0.119***	0.116***	0.043*	−0.090***
	(0.021)	(0.049)	(0.034)	(0.042)	(0.030)	(0.037)	(0.041)	(0.037)	(0.025)	(0.020)
Constant	1.628	6.179	−5.198	−3.552	−0.591	−2.211	1.950	−2.631	2.402	2.025
	(2.191)	(4.539)	(4.089)	(4.330)	(2.309)	(2.066)	(4.836)	(3.565)	(2.663)	(2.166)
Observations	36	36	36	36	36	36	36	36	36	36
R^2	0.926	0.534	0.642	0.652	0.875	0.924	0.834	0.821	0.885	0.927
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 12: Carry Trade Returns Regression Results (Post-Crisis: Jan 2010 - Jul 2015)

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.213***	0.854***	0.580***	0.539***	1.328***	0.981***	0.992***	1.207***	1.103***	1.203***
	(0.074)	(0.086)	(0.075)	(0.131)	(0.153)	(0.068)	(0.106)	(0.090)	(0.072)	(0.073)
IML	−0.069**	0.064*	0.139***	−0.203***	−0.196***	0.185***	0.182***	0.045	0.051*	−0.069**
	(0.034)	(0.035)	(0.034)	(0.046)	(0.069)	(0.032)	(0.036)	(0.031)	(0.029)	(0.033)
Constant	0.482	−2.022	0.767	2.788	−1.066	1.025	−1.615	2.227	−1.009	0.424
	(1.818)	(2.046)	(1.761)	(3.612)	(2.091)	(1.857)	(2.656)	(1.964)	(2.076)	(1.823)
Observations	67	67	67	67	67	67	67	67	67	67
R^2	0.845	0.667	0.771	0.522	0.672	0.876	0.815	0.845	0.852	0.844
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 13: Carry Trade Regression with MKT.PC1 as Risk Factor (Whole Sample: Jan 1999 - Jul 2015)

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{MKT.PC1,j} MKT.PC1_t + \varepsilon_{j,t}$$

$\beta_{AER,j}$ is the factor loading of the market risk factor defined as the first principal component of all the ten currencies. The market risk factor is interpreted as the average excess FX rate of return for a U.S. investor who goes long in all the currencies. $\beta_{MKT.PC1,j}$ is the factor loading of the proxy liquidity risk factor, MKT.PC1. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2 and N is the number of observations.

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.119***	0.707***	0.728***	0.394***	1.026***	1.281***	1.270***	1.135***	1.227***	1.112***
	(0.034)	(0.048)	(0.055)	(0.074)	(0.053)	(0.056)	(0.063)	(0.047)	(0.039)	(0.034)
MKT.PC1	−0.352	0.686**	0.732**	−1.672***	−0.917***	1.435	1.586	0.602*	0.221	−0.322
	(0.222)	(0.312)	(0.357)	(0.484)	(0.343)	(1.367)	(1.414)	(0.308)	(0.254)	(0.221)
Constant	0.102	1.176	−0.777	−1.677	−1.631	1.210	1.282	1.747	0.320	0.248
	(1.007)	(1.417)	(1.620)	(2.195)	(1.558)	(1.668)	(1.878)	(1.399)	(1.155)	(1.005)
N	199	199	199	199	199	199	199	199	199	199
R^2	0.849	0.553	0.502	0.551	0.660	0.736	0.685	0.759	0.840	0.848
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 14: Carry Trade Regression with MKT.PC1 as Risk Factor (Crisis: Jan 2007 - Dec 2009)

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.101***	0.620**	0.858***	0.215	0.937***	1.548***	1.462***	0.932***	1.236***	1.090***
	(0.132)	(0.243)	(0.146)	(0.199)	(0.186)	(0.093)	(0.142)	(0.157)	(0.120)	(0.134)
MKT.PC1	−0.567	0.837	1.158**	−1.420	−0.960	1.047	1.064	1.213**	0.251	−0.530
	(0.501)	(0.945)	(0.584)	(1.028)	(0.586)	(1.462)	(1.787)	(0.538)	(0.516)	(0.507)
Constant	1.545	5.245	−6.636	−4.653	−1.496	1.164	4.924	−4.387	2.561	1.734
	(2.028)	(3.932)	(5.200)	(5.979)	(2.998)	(3.842)	(5.681)	(3.348)	(2.790)	(2.144)
N	36	36	36	36	36	36	36	36	36	36
R^2	0.877	0.478	0.583	0.591	0.652	0.873	0.782	0.764	0.875	0.873
Note:										*p<0.1; **p<0.05; ***p<0.01

Results of pre-crisis and post-crisis are available in the Internet Appendix.

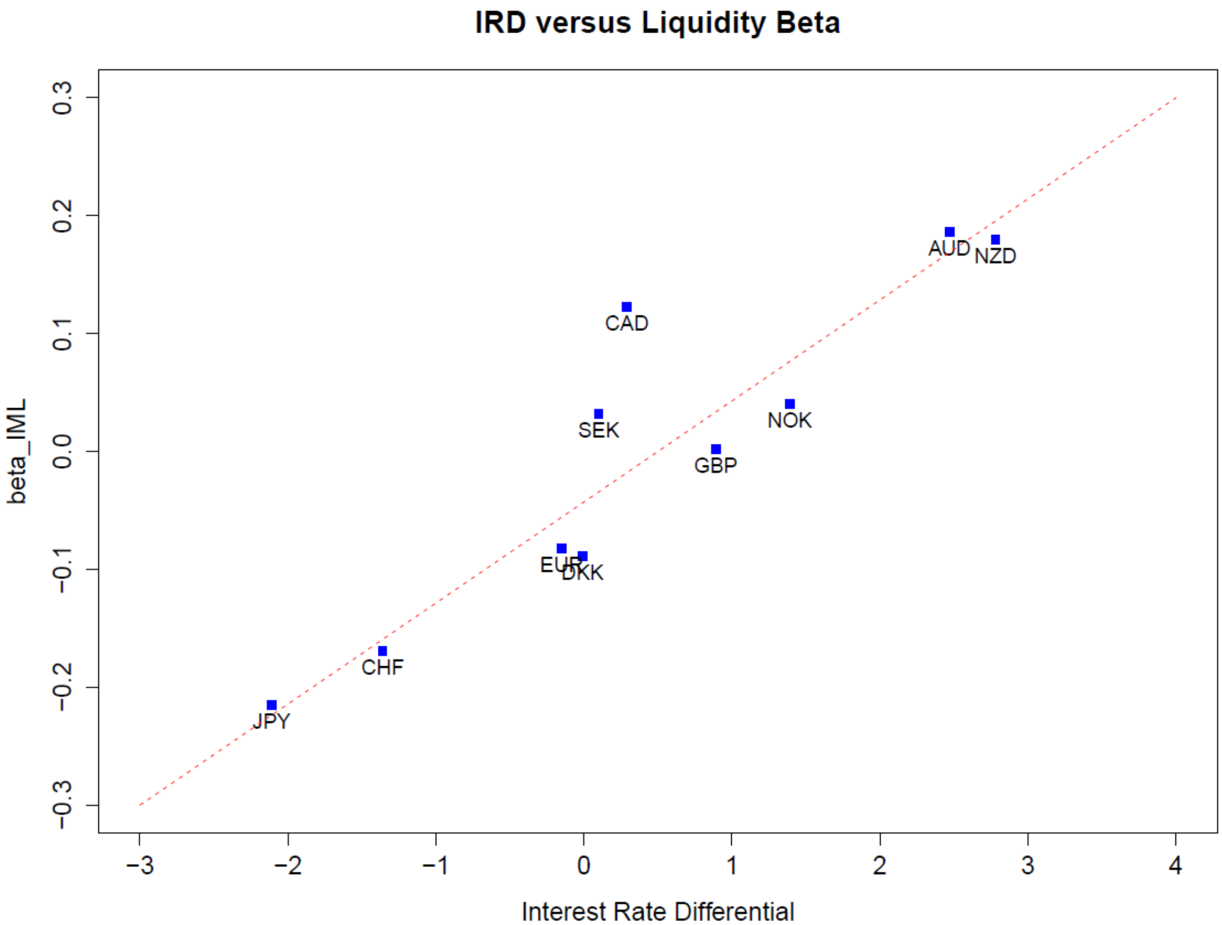

Figure 2: Interest Rate Differential (IRD) and Liquidity Risk Sensitivity.

This graph shows interest rate differential on the horizontal axis $i^f - i^d$, and liquidity beta on the vertical axis, β_{IML}. IML is a currency portfolio that is long in the most four illiquid currencies and short in the most four liquid currencies. Sample is from January 1999 to July 2015. JPY and CHF are low interest rate currencies with the lowest liquidity betas. AUD and NZD are high interest rate currencies with the highest liquidity betas.

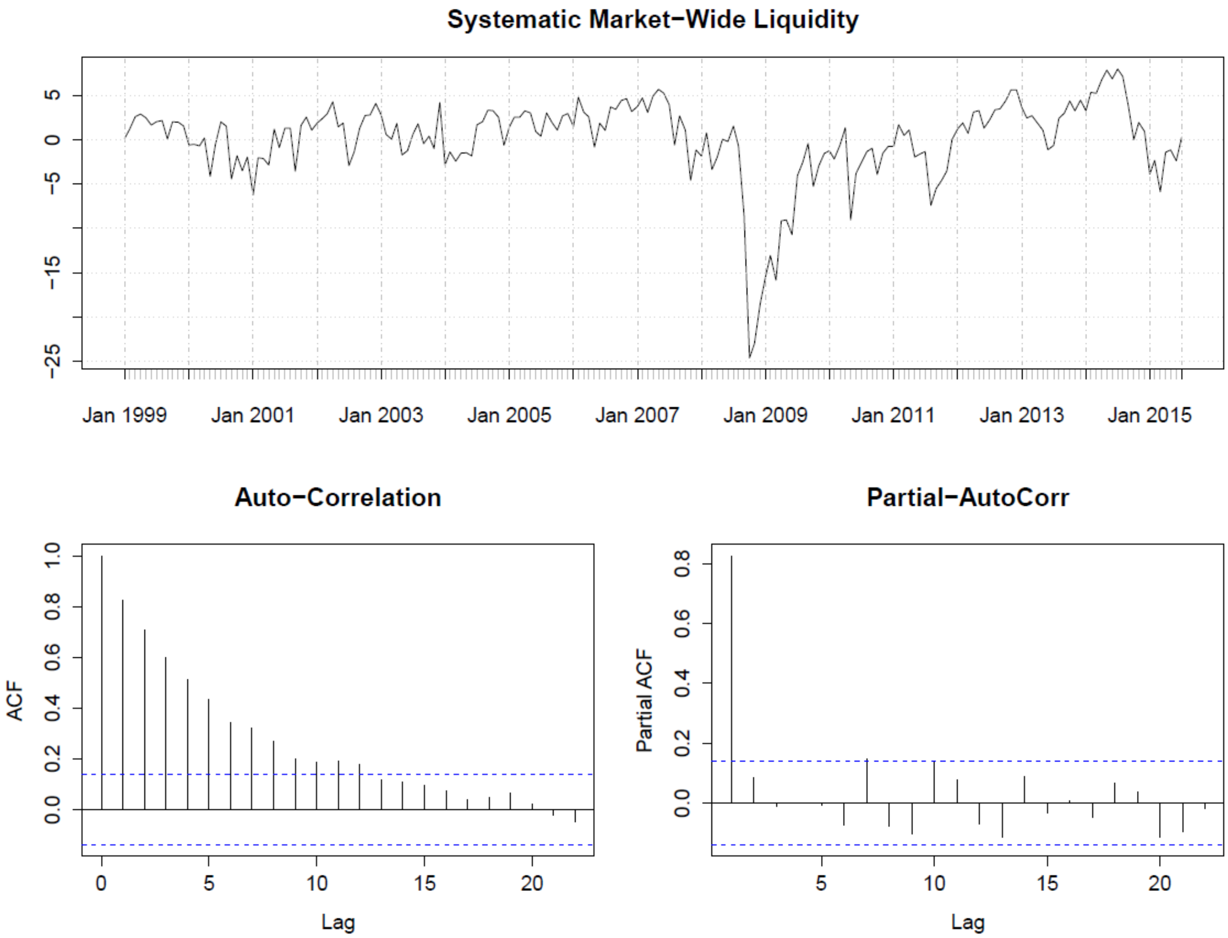

Figure 3: Autocorrelation and Partial-Autocorrelation of Systematic Market-Wide Liquidity.

The top graph depicts the systematic market-wide liquidity measure. Bottom graphs show the autocorrelation (ACF) and partial-autocorrelation (PACF) of the systematic market-wide liquidity measure. The PACF shows that residuals of AR(1) should be used as a proxy risk factor.

Table 15: Carry Trade Regressions with Innovations (Whole Sample: Jan 1999 - Jul 2015)

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{Resid.MKT,j} Resid.MKT_t + \varepsilon_{j,t}$$

$\beta_{AER,j}$ is the factor loading of the market risk factor defined as the first principal component of all the ten currencies. The market risk factor is interpreted as the average excess FX rate of return for a U.S. investor who goes long in all the currencies. $\beta_{Resid.MKT,j}$ is the factor loading of the proxy liquidity risk factor, Resid.MKT. Liquidity risk factor, Resid.MKT, is the residuals of AR(1) model fitted to MKT.PC1. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2 and N is the number of observations.

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.136***	0.711***	0.690***	0.427***	1.057***	1.237***	1.258***	1.117***	1.234***	1.132***
	(0.042)	(0.067)	(0.060)	(0.087)	(0.072)	(0.052)	(0.070)	(0.068)	(0.046)	(0.044)
Resid.MKT	−1.142***	0.596	0.458***	−3.302**	−2.386***	2.358***	1.183	1.465**	0.032	−1.199***
	(0.390)	(0.660)	(0.136)	(1.336)	(0.839)	(0.683)	(0.861)	(0.584)	(0.452)	(0.369)
Constant	−0.080	1.122	−0.662	−1.791	−1.406	1.427	1.397	1.759	0.556	0.079
	(0.987)	(1.358)	(1.479)	(2.224)	(1.305)	(1.593)	(1.971)	(1.196)	(1.128)	(0.989)
N	198	198	198	198	198	198	198	198	198	198
R^2	0.857	0.545	0.529	0.461	0.676	0.754	0.687	0.763	0.845	0.857
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 16: Carry Trade Regressions with Innovations Risk (Pre-Crisis: Jan 1999 - Dec 2006)

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.165***	0.783***	0.489***	0.690***	1.148***	1.046***	1.109***	1.135***	1.266***	1.169***
	(0.050)	(0.061)	(0.083)	(0.128)	(0.058)	(0.089)	(0.093)	(0.079)	(0.062)	(0.048)
Resid.MKT	−1.495**	0.776	0.345	−0.242	−1.578*	1.903	2.925*	1.169	0.144	−1.541**
	(0.657)	(1.089)	(0.945)	(1.109)	(0.948)	(1.461)	(1.745)	(1.093)	(0.694)	(0.640)
Constant	−0.213	0.521	−2.070	−1.624	−1.922	1.447	1.917	1.247	0.638	0.057
	(1.222)	(1.531)	(2.112)	(2.833)	(1.484)	(2.371)	(2.882)	(2.097)	(1.556)	(1.206)
N	95	95	95	95	95	95	95	95	95	95
R^2	0.869	0.571	0.472	0.495	0.788	0.561	0.561	0.694	0.826	0.871
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 17: Carry Trade Regression with Innovations (Crisis: Jan 2007 - Dec 2009)

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{Resid.MKT,j} Resid.MKT_t + \varepsilon_{j,t}$$

$\beta_{AER,j}$ is the factor loading of the market risk factor defined as the first principal component of all the ten currencies. The market risk factor is interpreted as the average excess FX rate of return for a U.S. investor who goes long in all the currencies. $\beta_{Resid.MKT,j}$ is the factor loading of the proxy liquidity risk factor, Resid.MKT. Liquidity risk factor, Resid.MKT, is the residuals of AR(1) model fitted to MKT.PC1. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2 and N is the number of observations.

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.149***	0.621**	0.651***	0.448***	1.090***	1.405***	1.493***	0.758***	1.238***	1.147***
	(0.120)	(0.256)	(0.171)	(0.153)	(0.205)	(0.086)	(0.176)	(0.149)	(0.151)	(0.124)
Resid.MKT	−1.505*	0.899	1.078***	−5.842***	−3.857***	2.586***	1.501	4.539***	0.230	−1.627**
	(0.833)	(1.648)	(0.242)	(1.829)	(1.299)	(0.959)	(1.504)	(1.040)	(1.269)	(0.783)
Constant	0.595	1.820	−1.468	−2.197	−1.947	−1.317	2.627	−1.521	3.370	1.038
	(2.362)	(2.626)	(1.622)	(2.686)	(2.829)	(1.303)	(2.047)	(3.061)	(2.920)	(2.201)
N	36	36	36	36	36	36	36	36	36	36
R^2	0.881	0.658	0.676	0.575	0.715	0.892	0.783	0.837	0.874	0.880
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 18: Carry Trade Regression with Innovations Risk (Post-Crisis: Jan 2010 - Jul 2015)

	Dependent variable:									
	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AER	1.090***	0.697***	0.813***	0.220	0.997***	1.288***	1.334***	1.265***	1.217***	1.079***
	(0.066)	(0.052)	(0.065)	(0.138)	(0.133)	(0.072)	(0.085)	(0.058)	(0.062)	(0.065)
Resid.MKT	−0.077	1.841***	0.788	−2.055	−0.978	1.147	0.664	1.001	0.945	−0.057
	(0.926)	(0.622)	(1.553)	(1.610)	(2.184)	(0.827)	(1.137)	(1.011)	(0.708)	(0.913)
Constant	0.276	−1.722	1.345	3.711	−2.848	1.819	−1.295	2.605	−1.114	0.222
	(1.910)	(2.031)	(2.149)	(4.074)	(3.328)	(2.579)	(3.126)	(2.211)	(2.077)	(1.907)
N	67	67	67	67	67	67	67	67	67	67
R^2	0.830	0.665	0.687	0.352	0.570	0.806	0.750	0.842	0.848	0.828
Note:										*p<0.1; **p<0.05; ***p<0.01

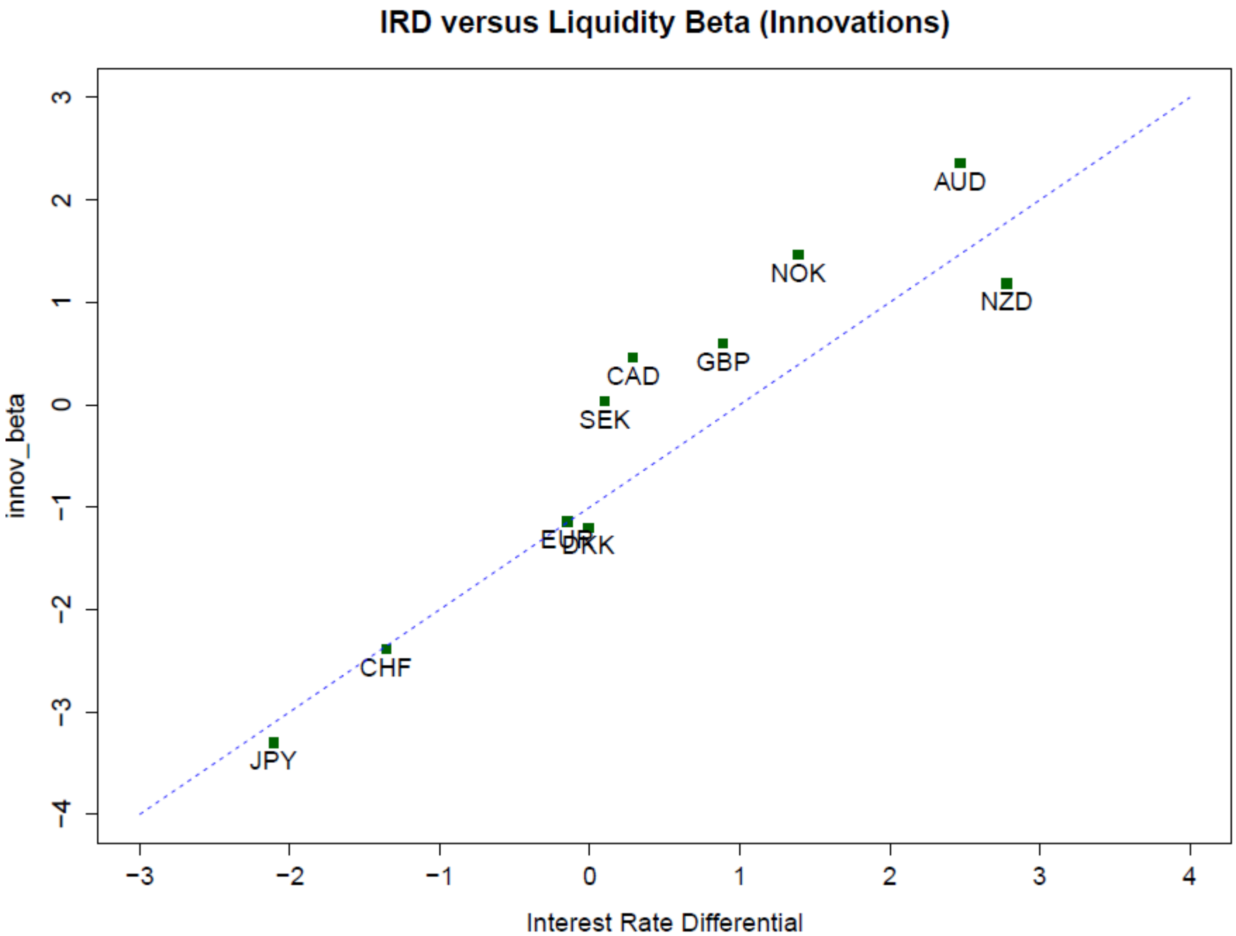

Figure 4: Interest Rate Differential (IRD) and Innovations Risk Sensitivity.

This graph shows interest rate differential on the horizontal axis $i^f - i^d$, and innovations beta on the vertical axis, β_{IML}. IML is a currency portfolio that is long the most four illiquid currencies and short the most four liquid currencies. Sample is from January 1999 to July 2015. JPY and CHF are low interest rate currencies with the lowest liquidity betas. AUD and NZD are high interest rate currencies with the highest liquidity betas.

Table 19: Economic Significance of Liquidity Betas, β_{IML}

EUR	**GBP**	**CAD**	**JPY**	**CHF**	**AUD**	**NZD**	**NOK**	**SEK**	**DKK**
Whole Sample (Jan 1999 - Jul 2015									
-0.235	0.006	0.367	-0.618	-0.433	0.393	0.368	0.096	0.076	-0.236
Pre-Crisis (Jan 1999 - Dec 2006)									
-0.252	0.148	0.312	-0.356	-0.351	0.522	0.467	0.061	0.032	-0.250
Crisis (Jan 2007 - Dec 2009)									
-0.290	0.345	0.364	-0.962	-0.604	0.670	0.574	0.375	0.123	-0.302
Post-Crisis (Jan 2010 - Jul 2015)									
-0.069	0.064	0.139	-0.203	-0.196	0.185	0.182	0.045	0.051	-0.069

Economic significance shows the change in carry trade returns (in number of standard deviations) in response to an increase of one standard deviation in the tradable liquidity risk factor, IML. For example, when IML decreases by one standard deviation, AUD depreciates by 0.39 standard deviations, whereas JPY appreciates by 0.62 standard deviations for the whole sample. Following Chan et al. (1998), IML has the largest return volatility, implying that it captures the highest amount of factor risk as measured by the volatility of the spread in returns between the long and short positions.

Table 20: Deutsche Bank's G10 Currency Harvest (DBV) Carry Trade Fund (Whole Sample & Crisis)

This table reports time-series regression results for the monthly 2-Factor model, mimicking equation (15) with excess carry trade return replaced with DBV. Models (1) to (3) represent the whole sample and (4) to (6) for the crisis regime.

$$DBV^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{IML,j} IML_t + \varepsilon_{j,t}$$

	Dependent variable:					
	DBV					
	(1)	(2)	(3)	(4)	(5)	(6)
AER	0.015***	0.042***	0.039***	0.021*	0.060***	0.043***
	(0.005)	(0.008)	(0.006)	(0.011)	(0.017)	(0.015)
IML	0.022***			0.022***		
	(0.001)			(0.003)		
MKT.PC1		0.138**			0.120	
		(0.066)			(0.083)	
Resid.MKT			0.322***			0.455**
			(0.104)			(0.178)
Constant	0.563	0.328	0.327	0.218	0.117	0.036
	(0.788)	(0.461)	(0.453)	(0.267)	(0.457)	(0.410)
Observations	198	198	198	36	36	36
R^2	0.770	0.334	0.370	0.860	0.473	0.570
Note:				*p<0.1; **p<0.05; ***p<0.01		

Results of pre-crisis and post-crisis are available in the Internet Appendix.

Table 21: Cross-sectional pricing analysis (Fama-MacBeth procedure)

Estimations are done using the Fama-MacBeth procedure with 60-months of rolling betas. LIQ is the systematic liquidity risk factor. AER is the dollar risk factor (Average Excess Returns) and is calculated as the average of the cross-sectional portfolios' monthly excess returns. HML is the Lustig et al. (2011) carry risk factor, which is the return of a strategy that is long in the high-interest rate portfolio and short in the low-interest rate portfolio. The estimated coefficients reported are annualized and the t-statistics are corrected with the Shanken (1992) adjustment. The t-statistics are reported in parenthesis. The p-values of the χ^2 test for the null hypothesis of zero pricing errors are adjusted according to Shanken (1992). Following Lustig et al. (2011), a constant is included in the cross-sectional regressions, but it is only reported when it is statistically significant.

$$\bar{r}^e_{j,t} = \beta_j^{LIQ}\lambda_t^{LIQ} + \beta_j^{Other}\lambda_t^{Other} + \varepsilon_{j,t} \qquad \text{for t=1, ...,T}$$

Panel A: Systematic Liquidity Risk Factor

	LIQ	R^2	χ^2
λ	0.0412	65.87	0.6428
t-statistic (SH)	(3.0584)		

Panel B: Systematic Liquidity Risk & Dollar Risk Factors

	LIQ	AER	R^2	χ^2
λ	0.0385	0.0401	68.54	0.2129
t-statistic (SH)	(3.0967)	(1.8596)		

Panel C: Systematic Liquidity Risk & Carry Risk Factors

	LIQ	HML	R^2	χ^2
λ	0.0393	0.0322	77.35	0.3034
t-statistic (SH)	(3.2362)	(0.8236)		